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State Health Expenditure and Infant Mortality in India

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Spending to Save? State Health Expenditure and Infant Mortality in India

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Abstract
There are severe inequalities in health in the world, poor health being concentrated amongst poor people in poor countries. Poor countries spend a much smaller share of national income on health expenditure than do richer countries. What potential lies in political or growth processes that raise this share? This depends upon how effective government health spending in developing countries is. Existing research presents little evidence of an impact on childhood mortality. Using specifications similar to those in the existing literature, this paper finds a similar result for India, which is that state health spending saves no lives. However, upon allowing lagged effects, controlling in a flexible way for trended unobservables and restricting the sample to rural households, a significant effect of health expenditure on infant mortality emerges, the long run elasticity being about -0.24. There are striking differences in the impact by social group. Slicing the data by gender, birth-order, religion, maternal and paternal education and maternal age at birth, I find the weakest effects in the most vulnerable groups (with the exception of a large effect for scheduled tribes).

Keywords: public spending, health, poverty, infant mortality, India

JEL Classification: I12, J13, C33

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1. Introduction

1.1. Motivation and Context

Inequalities in life expectancy across and within countries are created mainly by variation in childhood mortality. In poor countries, 30% of deaths are amongst children, compared with less than 1% in rich countries (Cutler et al. 2005, p.15). As many as 10 million children under the age of five die each year, mainly from preventable (or curable) conditions that seldom kill children in rich countries (Jones et al. 2003, Black et al. 2003). Yet most of the relevant interventions, such as immunization or oral rehydration therapy, are very low-cost (e.g. Deaton 2006b). This suggests that it is not just a question of raising incomes, but of the effective delivery of publicly provided health services. In this paper the effectiveness of public intervention (state health expenditure) is measured in terms of its impact on infant mortality, or death in the first year of life.

The analysis is conducted for India, which accounts for one in four of under-5 deaths, one in three of the poor and one in six of the population in the world. On account of its size, it has the highest child death toll in the world: 2.4 million under-five deaths (Black et al. 2003), and infant deaths account for more than two-thirds of these. Infant mortality is regarded as a sensitive indicator of the availability, utilisation and effectiveness of healthcare, and it is commonly used for monitoring and designing population and health programmes (The Tribune, 2002). Like the United States, India has a federal political structure, and health is a "state subject", which means that the level and allocation of health expenditure are decided at the state level.

Analyses of the historical decline in childhood mortality rates in today's industrialised countries suggest that important drivers of this decline were improved nutrition, public health, and medical technological progress (see Fogel 2004, Cutler and Miller 2005, Cutler et al. 2006). Improved nutrition tends to be associated with growth in income. Medical progress may, in principle, diffuse across geographic boundaries with no tight connection to incomes or public expenditure. Improvements in education, water and sanitation, immunization and targeted programmes against diseases like malaria and diarrhoea tend to be associated with growth in public spending.

In assessing the role that public spending might play in bringing down childhood death in poor countries, it is important to disentangle its effects from those of other trended variables, in particular, income growth and scientific progress. This is done here by investigating the impact on infant mortality of fluctuations in health expenditure around a state-specific trend. Although the conventional wisdom is that fiscal policy should be counter-cyclical, smoothing the effects of income shocks (Lane 2003), in practice it is often pro-cyclical in developing countries (Woo 2005). At the same time, aggregate income volatility is much greater in poor than in rich countries (Pritchett 2000, Koren and Tenreyro 2007). In these circumstances, we may expect that mortality is counter-cyclical, with adverse shocks to household income being reinforced by cuts in social expenditure. For the Indian sample analysed here, this is the case (Bhalotra 2007). This paper isolates the impact on mortality of changes in state health expenditure, holding constant state income. The effect I identify is therefore the effect of changes in the share of state income that is dedicated to health. This may vary, for example, in response to health shocks (natural disasters, rainfall variation, epidemics), inequality (Woo 2005), the political climate in the state, and the salience of public health.

I use individual data on mortality derived from retrospective fertility histories recorded in a national sample survey and merged by birth-cohort with a twenty-nine year panel of data on state health expenditure, income and other variables. The individual data are, in this way, "nested" in a state-year panel. The main contributions of this paper over the existing literature lie in its exploiting sub-national panel data on health expenditure to identify its impact, and its use of individual data on mortality to investigate heterogeneity in this impact by social group. Let me elaborate each. Most previous studies use a single section of cross-country data (see section 1.2). They are therefore unable to control for unobservable trends in medical technology which have been important in driving mortality reduction, and omission of which will tend to bias the estimated effects of health expenditure.[1] Cross-country regressions are also prone to other forms of correlated heterogeneity which, in a panel, are absorbed by state fixed effects. A further advantage of using a panel and, especially, a long panel, is that

[1] Deaton and Paxson (2004), for example, emphasise the importance of controlling for time-varying unobservables in identifying the impact of income on mortality.

dynamics can be explored. No previous research in this domain appears to have explored dynamics and, here, I show that this is critical. This is also the first study in this area that controls for correlated weather shocks, omission of which will generate spurious co-variation of mortality and health expenditure. Only a couple of previous studies have examined heterogeneity in the impact of health expenditure on health outcomes and, this, by (simulated) income groups (Gupta et al 2003, Bidani and Ravallion 1997). This study investigates heterogeneity by observed individual and family characteristics. This is interesting in itself but it also provides insight into the mechanisms by which health expenditure has an impact, if any.

Using specifications similar to those in the existing literature, I find the result highlighted in the literature, which is that state health spending saves no lives (see Filmer and Pritchett 1999). However, restricting the sample to rural households (more than two-thirds of all) and conditioning upon state-specific trends, a significant effect emerges that is driven by the third lag of health expenditure. The long run marginal effect is -0.023 and, with average mortality in the sample at about 9.5%, the elasticity is -0.24. A one standard deviation (0.48) increase in log health expenditure per capita at a given level of state income is estimated to reduce the risk of mortality by 1% which, taking a UN estimate of live births in India in 1990 of 26.3 million, amounts to saving 0.26 million lives.

There are striking differences in the impact of health expenditure by social group. The impact is greater for rural and scheduled tribe households than for urban or higher-caste households. This is consistent with more remotely located people benefiting from marginal increases in health expenditure. However, slicing the data by gender, birth-order, religion, mother's and father's education and maternal age at birth, I find weaker effects in the more vulnerable groups. I argue that this may be related to the way in which health expenditure is used. Previous studies that have looked at the distribution of health expenditure effects have focused on income. The effects I find suggest that attitudes and information, which may not be strongly correlated with income, mediate the effects of state spending.

1.2. Related Literature

When Peru's GDP fell in 1987-90 by 30%, government health expenditure fell by 58%, its budget-share falling from 4.3 to 3%. At the same time, infant mortality spiked, rising by 2.5 percentage points (Paxson and Schady 2005). While this is one of the most persuasive analyses in the literature, describing trends broken by a big exogenous shock, it is difficult to generalise from. In particular, changes in health expenditure might impact mortality only when they are very large. There is limited evidence on the health effects of year to year fluctuations in state health spending since most previous studies have used a single section of cross-country data.

In an influential study, Filmer and Pritchett (1999) investigate the effect of government health expenditure on infant and under-5 mortality using cross-sectional data on 98 developing countries in 1992/3. They find a very small and statistically insignificant effect. They show that 95% of the variation in mortality between countries is explained by income per capita, income inequality, female education, ethnic fractionalisation, and whether the country is more than 90% Muslim. This is an important study with striking results. But the results are not incontrovertible. Using data for 50 developing and transition countries observed in 1994, Gupta et. al. (2002) find some evidence that government health expenditure is negatively correlated with childhood mortality, but they show that this relationship is not robust. Using cross-sectional data for 22 developing countries in 1985, Anand and Ravallion (1993) find that health expenditure raises life expectancy and that, conditional upon this, income has no effect. All of these studies suffer two important limitations, which the authors recognise. First, data on both mortality and government health expenditure are unlikely to be comparable across countries. Second, the estimates in these studies are subject to bias on account of unobserved heterogeneity that might be correlated with the variable of interest (see Durlauf et al. 2005). The present study addresses the first problem by using sub-national data, and the second problem by using panel data on state health expenditure and income.

There is some relevant recent work for India (Deolalikar 2005). Using a state panel for 1980-99, this study finds no effect of current health expenditure on mortality rates once state fixed effects and a linear time trend are included in the model. I find a similar result (see below). Anil Deolalikar further investigates the relationship for a reduced sample of four years and fourteen states (N=56) for which information on female literacy is available. For this sample, an interaction term between health expenditure and state income is included and the results suggest a negative effect of health expenditure but only in the poor states. In a complementary analysis of micro-data for the period 1994-1998, he finds the opposite- that the effects of health expenditure are weaker in the poor states. My state-specific estimates show no very clear relation between the effects of health expenditure and the per capita income of the state. However, there are differences between the two studies in sample period, data and estimator. In particular, this study uses a longer time period and a more flexible specification of trends, it conditions upon rainfall shocks, and it investigates lagged effects. It also investigates heterogeneity in the impact of health expenditure.

The rest of this paper is organised as follows. Section 2 describes the data and Section 3 presents relevant descriptive statistics. An empirical model is set out in Section 4 and results are discussed together with a range of robustness checks in Section 5. Section 6 concludes.

2. The Data

The micro-data are derived from the second round of the National Family Health Survey of India (NFHS-2)[2]. This contains complete fertility histories for ever-married women aged 15-49 in 1998-99, including the time and incidence of child deaths. I use these to construct individual-level indicators of infant mortality. The children in the sample are born in 1961-1999. I drop births in the 1960s since these data are thin and skewed (see below). To ensure that every child is allowed full exposure to the risk of infant mortality, births that occur in the 12 months preceding the survey are excluded. The estimation sample contains more than 150000 children of more than 59000 mothers born in 1970-1998 across the 15 major Indian states. These micro-data are merged by state and year of birth with a panel of data on health expenditure and other relevant statistics for the 15 Indian states.[3]

State health expenditure includes expenditure from state revenue (85%) and central government health allocations to the state (15%), the latter often being tied to public health and family welfare programmes. I use actual as opposed to budgeted

[2] For details on sampling strategy and context, see IIPS and ORC Macro (2000). The data are available at www.measuredhs.com.

[3] I am grateful to Tim Besley and Robin Burgess for letting me use their state-level panel (see Besley and Burgess 2002, 2004, for example). Detailed definitions of the state-level variables used in these analyses can be found at http://sticerd.lse.ac.uk/eopp/research/indian.asp and in the Appendices of the papers cited there. The health expenditure series were kindly given to me by Juan Pedro Schmid, who gathered them from Reserve Bank of India publications. Juan made the series consistent before and after 1985, the year in which the published categorisation of health expenditure was changed. Before 1985, state health expenditure included expenditure on medical and public health, family planning and water supply and sanitation. From 1985 onwards, family planning and water-sanitation expenditures appear separately in the accounts and need to be added in.

revenue expenditure, even if this makes it more likely that health expenditure is endogenous. State health spending covers rural and urban public health services; medical education, training and research; general administration; water supply and sanitation; and family welfare. The expenditure series is cast in per capita termsand deflated by the consumer price index for agricultural workers. State income is measured as net domestic product and is subject to the same deflators. The NFHS provides a rich set of individual-level controls, which are included in the model to control for heterogeneity in death risk. There are no data on household incomes over the 28-year period analysed. Permanent income at the household level is proxied by parental education, and also caste and religion. Note that the educational attainment of parents varies by cohort of child and, in this way, it varies over time. The estimates control for aggregate income at the state level, which finances state health expenditure.

A strength of the mortality data is that they are annual and cover a long period. This is unusual (see Pritchett and Summers 1996). However, they have their weaknesses. The rest of this section discusses the way in which these potential problems are addressed. As the microdata are constructed from retrospective fertility histories, they are wedge-shaped, there being fewer observations for children born earlier in time. Moreover, the thinning of the data does not occur randomly, but is a function of maternal age at birth. I therefore condition upon maternal age at birth. Another issue that arises with retrospective data is that the mother may have migrated between states between the birth of the index child and the date of interview. However the survey asks the mother how long she has lived in her current location. Using this information, the analysis is restricted to the 85.1% of births that occurred in the mother's current location, so that we can be confident that infant mortality risk is related to health expenditure in the state in which the child was born. As a (rough) check on whether this sample selection is endogenous, I compared estimates on the restricted and unrestricted samples, and found that they were not significantly different. The conventional definition of infant death is death before the first birthday of the child. Since mother's reports of age at death of their children exhibit age-heaping at six-monthly intervals, infancy is defined here to include the twelfth month. The results are not sensitive to this difference, but the inclusive definition is retained since this increases the ratio of ones to zeroes in the dependent variable.

3. Descriptive Statistics

To obtain descriptives, I aggregated the individual data to the state level using sampling weights. The aggregation is done by birth cohort, yielding a straightforward panel in which state mortality rates can be related to state health expenditure. Figures 1-4 show the dispersion in levels and trends across the states in mortality, state health expenditure, the share of health expenditure in state income, and income. The rate of increase in the level and share of state health expenditure has slowed since about the mid-1980s, even as the growth rate of state income has increased. Regressing state health expenditure on state income, a lagged dependent variable (instrumented with two further lags), year and state dummies and state-specific trends, I find a long run income elasticity of health spending of -0.41. This is identified fom within-state variation. An elasticity smaller than one indicates that the share of health expenditure in income is decreasing in income.[4] . Government health expenditure in India was, on average, 1.3% of GDP in 1990, and this had declined to 0.9% in 1999 (NRHM 2005). India devotes a smaller share of its income to health spending than, for example, Bangladesh (1.4%) or Sri Lanka (1.8%) (Deolalikar 2005: chapter 2; these are figures for the year 2000), and it spends a disproportionate part of its health budget on (curative) hospital services which are less pro-poor than (preventive) public health expenditures (Peters et al. 2002).

Figure 5 shows that the raw relationship between mortality and health expenditure is negative in most states. Figure 6 plots these data after removing state-specific trends. In the de-trended data, it is unclear that increases in health expenditure are associated with decreases in mortality. The rest of this paper explores whether these simple associations persist after conditioning upon other covariates, and allowing for lagged effects.[5]

4. The Empirical Model

The baseline model is

[4] I find a similar elasticity for state education expenditure; results available on request

[5] Growth rates of the main variables by state (Table A1) and summary statistics for all variables in the model (Table A2) are in an Online Appendix available at www.efm.bris.ac.uk/www/ecsrb/bhalotra.htm. Figures A1 and A2 in this Appendix describe inequality in the levels of mortality and health expenditure across the states.

$$(1)\ M^{*}_{imst}=a_0+a_s+a_t+m_{st}+b\ lnH_{st}+g\ lnY_{st}+h_s{}' R_{st}{}^{f}+g_s{}' R_{st}{}^{d}+l\,' X_{imst}+f\,' Z_{st}+e_{imst}$$

Subscripts *s* and *t* indicate state and year and *i* and *m* indicate the individual child and mother respectively, ln denotes logarithm. M^* is a latent variable measuring the probability of infant death, H is per capita real health expenditure, Y is per capita real net domestic product and b is the parameter of interest. X is a vector of variables observed at the child or mother level, Z is a vector of state-level controls and R^f and R^d are vectors of positive and negative state-specific rainfall shocks (superscripts f and d denote "flood" and "drought" respectively). To avoid clutter, I do not show dynamics or interaction (and quadratic) terms, though these are investigated, and discussed in the Results section. a_s and a_t are state and year fixed effects and m_{st} are state-specific trends.

The model is estimated as a probit. All reported standard errors are robust and clustered by state. These adjustments allow for conditional heteroskedasticity and for conditional autocorrelation within states (see Bertrand et al 2004, Cameron and Trivedi 2005, p.788). Note that adjusting for clustering at the state-level takes care of any lower-level clustering such as at the community or mother-level. Identification of b relies upon there being independent fluctuations in health expenditure within states. The relatively long time dimension of the data makes it more likely that this is the case.

X includes dummies for gender and birth-month of the child, age of mother at birth of the child, levels of education of each of mother and father, and ethnicity and religion of the household. These characteristics have been shown to be significant predictors of mortality risk in a number of previous studies, and also in India (e.g. Bhalotra and van Soest 2007). Z includes income inequality measured as the log of the Gini coefficient for each of the rural and urban sectors, poverty measured as the log of the sector-specific headcount ratio, the ratio of the log of agricultural to non-agricultural income in the state, inflation in consumer prices and a quadratic in newspaper circulation per capita.

Rainfall shocks are measured as the absolute deviation of rainfall in each state-year from its 30-year state-mean. A positive shock is defined as equal to this deviation when it is positive, and zero otherwise. A negative shock is symmetrically defined. These are the terms that appear in the regressions. To allow the effects of rainshocks on mortality to be different in different states, each of these two indicators is interacted with 15 state dummies, so that R is a vector of 30 variables. The richness of this specification is justified by the results. When rainshocks are restricted to have the same effect in every state, they are insignificant. Once state-specific coefficients are allowed, they are jointly significant at 1%. The results also show that it is restrictive to force positive and negative deviations to have the same effect.[6]

The panel aspect of these data offers some clear advantages. It is important that we are able to control for time-varying unobservables including medical technological progress. Failing to do so would result in over-estimation of the effects of any included trended variables (health expenditure, income). The assumption that time dummies capture technology trends is more plausible for states within a country than it is in a cross-country panel.[7] This assumption is further relaxed by including state-specific trends in the model. The time dummies also capture common (all-India) shocks such as famines, floods or epidemics, and the state-specific trends capture not only state-specific components of health technology but also other omitted trends, for example, in fertility, or public services. The state effects, $a_{S,}$ control for all forms of time-invariant unobserved heterogeneity specific to a state. In this context, this is likely to include sluggish political institutions, ethnic composition, geography, and initial conditions, including the initial level of mortality in the state. They will also pick up any persistent differences across the states in accounting conventions (measurement error).

Since health expenditure, the regressor of interest, varies by state-year, we cannot, of course, include state-year dummies to control comprehensively for state-specific health shocks. As a result, health expenditure remains potentially endogenous. Consider, for example, that a particular state suffers a flood or a drought. Suppose that,

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[6] A natural alternative to using absolute deviations is to use the z-score of rainfall which normalises deviations with respect to the standard deviation in the state. The specification used here allows a big deviation in rainfall to impact infant mortality as much in a state that often experiences rainfall fluctuations as it would in a state with a more stable weather pattern. This seems to me the more relevant specification, but I have confirmed that using z-scores does not alter the main results of this analysis.

[7] Temple (1999), for example, shows that countries have different rates of technical progress in growth regressions, casting doubt that technology is a public good. This said, diffusion of health technology across countries may occur more rapidly than diffusion of production technology.

as a result, more infants die, and the state reacts by raising health expenditure.[8] This will create a positive association of infant mortality and health expenditure in the data. To purge the data of this, I control in a flexible way for rainshocks. These are probably the most important sorts of health (and income) shocks given that most infant deaths are rural and rural households are more likely to be engaged in agriculture, and more likely to live in areas with poor sanitation where rainfall variation can directly affect disease epidemiology. I nevertheless also control for other state-level variables, omission of which may drive a spurious correlation between health expenditure and mortality. For instance, Woo (2005) argues that fiscal policy may be influenced by inequality; so inequality is one of the variables in the vector Z in equation (1). I also estimate a model in which current health expenditure is replaced by its first four lags. This makes it even less likely that the expenditure coefficient is biased by state-specific shocks that are not controlled for. Section 5.1 discusses substantive reasons to include lags.

Since the key regressor (state health expenditure) varies at the state and not the individual level, the data are a bit scarce for estimation of state-specific models. However, to gain at least an indicative sense of the state-specific relationships, I also estimate the following simple linear model for each state (T=28):

$$(2)\ M^{*}_{imt}=f_0 + h_t + c\ lnH_t + n\ lnY_t + h' R_t^f + g' R_t^d + l' X_{imt} + f' Z_t + u_{imt}$$

The notation is the same as in equation (1).

5. Results

Henceforth *health expenditure* refers to the logarithm of real per capita state health expenditure and *income* refers to the logarithm of real per capita net domestic product of the state.

5.1. Static Models

Table 1 presents marginal effects estimated from a probit for infant mortality (equation 1) using a (log)linear term in current health expenditure, a quadratic, and a first lag. The results for urban households show that health expenditure has no effect on infant mortality, whatever the specification and that income is also insignificant

[8] To investigate this directly, I estimated an auxiliary panel data model in which state health expenditure is the dependent variable. Controlling for state income, fixed effects and state-specific trends, I find that rainshocks are jointly significant at the 1% level.

once year dummies are included in the model (Table 1B). Infant mortality rates are higher in rural households and they are, on average, poorer and tend to have lower private expenditure on health and nutrition. We may therefore expect that state health expenditure is more effective for the rural sample. These results are in Table 1A. Although the unconditional correlation of mortality and health expenditure is now significant (-0.015), there is no effect once time effects are included. This result is unchanged if current expenditure is replaced by its first lag, but the second panel of Table 1A shows some evidence of (poorly-determined) non-linearity. It is interesting to see that mortality risk is hump-shaped in health expenditure, the relation turning negative at high levels of expenditure, with a marginal effect at the mean of -0.020. A possible explanation of this shape is that, at low levels of expenditure, most of it goes to politically prioritised areas such as curative care in urban areas, with bigger budgets extending to lower-priority areas such as preventive care, water supply or sanitation that are more likely to impact mortality at the margin (see Lanjouw and Ravallion 1999). I also investigated a specification in which health expenditure was interacted with income (as in Deolalikar 2005). The interaction term was negative but insignificant; these results are not displayed.

Marginal effects of income are also reported in Table 1. In the absence of controls for omitted trends, income has a significant marginal effect of -0.05 on rural mortality risk. Although this effect vanishes upon including time dummies (as did the health expenditure effect), it re-establishes itself (ME of -0.04) upon inclusion of state-specific trends (which health expenditure did not).[9] Dropping income raises the marginal effect of health expenditure but does not alter its significance level.

Rainshocks and micro-demographic variables are jointly significant, but dropping them from the model does not alter the health expenditure elasticity. Some of the state-level controls are significant but, again, conditioning upon them does not make a significant difference to the health expenditure effect. Each of the sets of state dummies, year dummies and state-specific trends is jointly significant at the 1% level in every specification in which they appear. As we have seen, the results *are* sensitive

[9] This result is consistent with state-specific trends capturing omitted variables that are positively correlated with mortality and health expenditure, but negatively correlated with income, for example, fertility. Alternatively, they might reflect trends in technology or in the delivery of public services. These might be negatively correlated with mortality and health expenditure and positively correlated with income, producing a similar configuration of results.

to conditioning upon time dummies and state-specific trends. The results are not sensitive to the choice of estimator. The linear probability model yields a similar pattern of results. Adjusting the standard errors for clustering by state increases them by about 43% (see Table A4 in the online appendix- refer footnote 5). The main conclusion of this section is that health expenditure has no effect on infant mortality once common time-varying unobservables are removed. Although the further specifications discussed below were estimated for both samples, there is no case in which health expenditure is significant for urban households. From here on, all reported results are therefore for the rural sample.

State-Specific Estimates of the Static Model

It is possible that these negative results conceal some significant state-specific slopes. To investigate this, I estimated state-specific models using the time series (equation 2). Results are in Table A3 in the online appendix. Health expenditure has a significant negative effect in three of the fifteen states (Assam, Maharashtra, West Bengal). If I drop state-specific trends, health expenditure is significantly negative in five states: Karnataka, Maharashtra, Tamil Nadu, Uttar Pradesh and West Bengal. These five states do not form a natural group in terms of being, for example, poorer, or more politically liberal. In contrast, the states that show a negative effect of income are the poorer, higher mortality states.

Distributed Lag Model

Although controlling for fixed effects and rainfall shocks removes some important sources of correlated unobserved heterogeneity, it remains possible that there are other state-specific health shocks that raise (or lower) both infant mortality and health expenditure, as a result of which the estimated coefficient on health expenditure will tend to carry a positive bias. This bias may be dominating an underlying negative causal effect in the results we have seen so far. I therefore investigated a distributed lag model that allows four lags of health expenditure. Using lags breaks any contemporaneous correlation between mortality and expenditure that is driven by an omitted variable, and it allows for the possibility that causal effects take time to play out. It is natural to allow the same lags for income.

The main effects are in Table 2; covariate effects are in Table A5 in the online appendix. Every column includes micro-demographics, rainfall shocks, state and time dummies and state-specific trends. Results are displayed with and without controlling for state-level variables. In the absence of state-trends, the inclusion of state-level covariates raises the coefficients on health expenditure and income, but it makes little difference once state-trends are included. The main finding is that the third lag of health expenditure and the third and fourth lags of income are significant. As this specification is asking rather a lot of the data, Table 3 reports estimates of a more parsimonious model that retains only the significant terms from the fourth-order lag specification. Now the marginal effect of health expenditure is -0.023 and the long run elasticity is -0.21. The long run income elasticity, at -0.28, is bigger. The effects of both health expenditure and income are sensitive to exclusion of the state-specific trends (see Table 3).

Replacing current with lagged values does not make a dramatic difference to the long run income effect, but it makes an important difference to the health expenditure effect (compare Tables 1A and 3). Health expenditure appears insignificant in most standard specifications, consistent with much of the existing literature. However, a sufficiently flexible model reveals a highly significant effect driven by the third lag of expenditure. What might explain this? Most infant death occurs in the first month and even the first week of life, and it is well known that the proximate cause of this is low birth-weight which, in turn, is largely explained by poor maternal health. So one lag may simply denote the importance of health expenditure in the year before birth (e.g. antenatal care). Since the first lag is not significant, it seems that there are further dynamics in the process. An example of a mechanism that may generate longer lags is state dependence in mortality within families. If a drop in state expenditure three years ago killed a sibling of the index child then this, in turn, may have a causal effect on the death risk of the index child (see Arulampalam and Bhalotra 2007). Alternatively, it may take longer than a year for increases in health spending to reach the ground.

To summarise the results so far, it is only when we restrict the sample to rural households, allow lags, and condition upon state-specific trends that a significant impact of health expenditure emerges. A possible explanation is that health expenditure is endogenous, and that this endogeneity is being limited by factoring out state-specific trends, and by lagging health expenditure. As for the rural-urban difference, it is well-known that failing to allow for heterogeneity can obscure important relationships in sub-populations. The estimated effects are likely to be conservative both because the survey only records births of mothers who survive until the survey date and because it records only live births. Both forms of selection may be expected to yield a sample of relatively healthy births.[10]

5.2. Robustness

We have already investigated robustness to functional form, lags, state-specific trends, rainfall shocks, state-level variables and micro-demographics. The rest of this section reports the results of further specification checks. First, I explored estimating the model on panel data by within groups (see Table 4). For this, the individual mortality information (0/1) was aggregated to the state level by cohort using sampling weights. An advantage of this is that it will average out unobserved heterogeneity. The health expenditure effect is a bit larger, but insignificantly different from that obtained in the analogous model run with micro-data on mortality. This suggests that the micro-demographic covariates in the model capture individual heterogeneity sufficiently well. Panel regressions in which the dependent variable is the log of infant mortality produce broadly similar results. I use the level rather than the log because it is more directly comparable with the baseline model estimated on individual data.[11] In the panel data specification, I allowed two lagged dependent variables to capture persistence in mortality, but these were insignificant. To investigate the hypothesis that significance of the third lag of health expenditure is in itself not meaningful but is proxying current health expenditure, I used the IV-Systems estimator, instrumenting current health expenditure by its second and third lag.[12] The marginal effect is -0.015 but it is insignificant, consistent with the results in Table 1.

Since the only significant results are for the rural sample, I replaced total state income with alternative measures of average income that are specific to the rural

[10] UN statistics on mortality rates are also calculated with reference to live births.

[11] If the individual-level mortality equation displayed in section 4 is cast as a linear probability model, aggregation to the state level will produce a specification in which the level (not log) of mortality is the dependent variable. Deaton (2006) argues that the interesting question is whether or not *income growth* causes the *level of mortality* to decline. He shows that evidence of such a relationship in cross-country data is much weaker than evidence of a relationship of income growth with *proportional* changes in mortality. If the same arguments apply when income is replaced with health expenditure (or share of), the specification estimated in this paper is the more conservative one.

[12] A GMM estimator (e.g. Arellano and Bond 1991) is not appropriate for the long and narrow panel here. It is more commonly used when N is large and T is small.

sector. The marginal effect of health expenditure is now larger, and remains significant. Relative to the benchmark model where the long run marginal effect of state income is -0.020, it is -0.025 if I use agricultural income, -0.029 if I use mean consumption and -0.030 if I use the rural wage. We have already conditioned upon a range of state-level variables (listed in section 4). Although I have also already conditioned upon the education level of parents, I further investigated conditioning upon state education expenditure. This is relevant to the extent that it is correlated with both infant mortality and state health expenditure. The coefficient on education expenditure is negative but insignificant, and the marginal effect of health expenditure is not altered.

5.3. Heterogeneity by Social Group

Having found significant heterogeneity by sector (rural/urban) in the health expenditure effect, heterogeneity by social class (micro-demographics) was further investigated for the sample of rural households. This is interesting in itself and provides insight into the underlying mechanisms. It is unusual in the literature relating social expenditures and outcomes, which is dominated by cross-country data analysis (section 1). The specification estimated is that in column 3 of Table 3 and results are in Table 5. Every slicing of the data produces a significant difference in the health expenditure effect. A general –and surprising- pattern that emerges is that health expenditure is *less* effective in reducing infant mortality in more vulnerable sections of society, that is, groups with relatively high mortality rates.[13] For example, the marginal effect is larger for boys, high caste children, Muslim children, higher-order births, children of educated mothers, and children born when the mother is in the relatively safe age range of 19-30 years. These differences are, of course, even larger when we look at the elasticity at the mean rather than at the marginal effect and, in most cases, health expenditure effects in the counterpart groups (girls, low caste etc) are insignificant (see Table 5).

The complete absence of any health expenditure effect for women with no education is striking because maternal education creates especially large differences

[13] Mortality rates and the sample contribution of each group are in Table 5. The reported percentages of children in each group will differ from, for example, census proportions of these social groups to the extent that there is differential fertility across groups. Also note that these are figures for rural India.

in mortality risk: average infant mortality of children of uneducated mothers is 10.4%, falling to 6.9% for mothers with some (non-zero) education, and to 3.5% for mothers with secondary or higher education. Educated mothers are likely to be better informed and so to extract a greater marginal advantage from a given level of health expenditure (see Jalan and Ravallion 2003). Similarly, prime-aged mothers might be more aware than teenage mothers, and Muslim mothers might exercise higher standards of sanitation within the home if regular prayer is associated with the requirement of regular washing. So it seems that heterogeneity in the health expenditure effect relates to how households use public resources and not necessarily to the distribution of these resources. This is supported by the results obtained by gender and birth-order. It is unlikely that there are systematic differences in the policy environment faced by, say, boys and girls. It is more likely that households allocate resources differently across children. In the case of gender, the results are consistent with the widely documented fact of son-preference in India. In particular, Basu (1989) shows that, conditional upon being sick, boys are more likely to be taken to a treatment-centre than are girls. In the case of birth-order, the results can be rationalised in terms of learning. If the first-born dies of diarrhea, the mother is more likely to learn about Oral Rehydration Therapy and use it to avert death for subsequent children.

There are two deviations from the pattern described so far, that is, two cases in which the more vulnerable group is more responsive to health expenditure. This, of course, is what we would expect on account of diminishing returns, and because better-off groups can afford to protect themselves against infant mortality even when state health services are weak. One case, that we have already encountered, is that health expenditure is more effective in rural than in urban areas. Mortality risk is 3.6 percentage-points higher for rural as compared to urban children. Even if health services are more sparse and variable in rural areas, there is greater scope for bringing down mortality. The other deviation is evident only when the low-caste group is sub-divided into its three components, which are scheduled castes (SC), scheduled tribes (ST) and "other backward classes" (OBC). State health expenditure has only small and insignificant effects on the SC and OBC groups, but it has a large negative effect on children of scheduled tribes (ST). Indeed, this is the largest marginal effect of any sub-group, about four times as large as the average effect in rural areas. The ST group are about 12% of the entire sample and 18% of the low-caste group. The infant mortality rate in the ST group is 10%, in contrast with 8.35% amongst high-caste Hindus. Scheduled tribes are thought to be the least integrated social group, historically having been isolated from community life, and tending to live in relative geographic isolation. This result is therefore quite striking.[14]

Some previous studies have found bigger impacts of state health expenditure on the poor (e.g. Bidani and Ravallion 1997, Gupta et al. 2003). As discussed in section 2, we do not have household income data.[15] Given the difficulties with measuring income for poor households (a large fraction of which are self-employed), it is useful to look at heterogeneity by other, more stable, indicators of social class. Since rural and ST households are clearly relatively poor, there is some support in these data for the view that state health expenditure is, at the margin, more beneficial to the poor. However, uneducated rural women are poor, and we find that health expenditure has no effect for this group. Father's education may be a better indicator of the permanent income of the household. But we find no significant variation in the health expenditure effects by father's education. Overall, with the exception of scheduled tribes, it seems that the most poor (rural and uneducated) and the better off (urban) do not benefit as much as the group in the middle (rural but educated).

The pattern of income effects is not the same as the pattern of health expenditure effects (Table 5). Indeed, in most cases, the differences are reversed. (Negative) income effects are larger for the more vulnerable groups. Recall that the effects of each of health expenditure and income are obtained conditional upon the other. This contrast between their distributional impact is consistent with complementarities between state health expenditure and personal attributes (education, information) that bias its effectiveness away from those individuals who need it most.

6. Conclusions

Infant mortality in rural India is significantly affected by variation in state health expenditure, given state income, and the long run elasticity is -0.24. We are unable to identify a corresponding effect amongst urban households. Failing to allow for heterogeneity, lagged effects and state-specific trended unobservables results in

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[14] Scheduled tribes distinguish themselves from other social groups (including the SC) in having lower infant mortality rates for girls as compared to boys. This may be pertinent, although why exactly is unclear.

[15] Nor do the two studies cited here. They estimate the distribution of effects under sometimes strong assumptions – discussed in Gupta et al. 2003.

under-estimation of the beneficial effects of health expenditure , and I have argued that this might explain some of the negative findings in the literature. The identified effect is robust to controls for state-specific rainfall shocks and other state-level variables including education, inequality and media prevalence. Although it is encouraging that it works on average, health expenditure appears to bring no benefit to some of the most vulnerable sections of society, a result that suggests complementarities between public and private (parental) inputs in the survival technology . It is widely recognised that the composition of state health expenditure is non-progressive, and that the share of public health, water and family welfare programmes in rural areas needs to be raised (section 2). The results in this paper suggest that, at the same time, it is important to educate adults in the use and the benefits of simple health-promoting technologies.

The effectiveness of health expenditure varies across the states, displaying a pattern that bears no evident relation to initial levels of mortality or income. A likely reason is that the states differ considerably in terms of initial conditions including inequality and infrastructure (e.g. Datt and Ravallion 2002). In the panel data model, these are captured by the state fixed effects. States also differ in terms of their political economy (e.g. Besley and Burgess 2002, Arulampalam et al. 2007). The effectiveness of public service delivery is increasingly recognised as being no less important than raising the quantity of expenditure (e.g. Besley 2006, Public Affairs Center 2002, World Bank 2003). A recent initiative of the central government of India, the National Rural Health Mission aims to undertake “architectural correction” of the health system, promoting service delivery, for example, by increasing decentralisation to the village level and instituting a female health activist in each village (see NRHM 2005). The NRHM also promises to raise the quantity of public health spending. The share of health expenditure in national income is only about 1% and it has decreased in the recent period of faster growth (see section 3). Under the NRHM it is expected to rise to “2-3% of GDP” in 2005-2012. The analysis in this paper needs to be repeated six years from now!

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Table 1: Probit Estimates of Infant Mortality using Alternative Specifications of Health Expenditure

Table 1A: Rural Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Health expenditure	**-0.015**	0.007	0.000	0.014	0.031	0.105			
	[1.92]	[0.57]	[0.03]	[0.66]	[1.22]	[1.28]			
Square of health expenditure				***-0.006***	-0.005	-0.018			
				[1.87]	[1.26]	[1.27]			
First lag of health expenditure							-0.012	0.015	0.008
							[1.63]	[1.58]	[0.91]
Income	**-0.051**	-0.028	**-0.037**	**-0.046**	-0.023	**-0.045**	**-0.055**	-0.026	**-0.038**
	[6.00]	[1.26]	[2.73]	[6.08]	[1.14]	[3.82]	[6.70]	[1.28]	[2.91]
State dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year dummies	×	✓	✓	×	✓	✓	×	✓	✓
State-specific trends	×	×	✓	×	×	✓	×	×	✓

Table 1B: Urban Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Health expenditure	-0.002	0.013	0.003	-0.022	-0.008	-0.055			
	[0.22]	[0.88]	[0.18]	[0.48]	[0.12]	[0.86]			
Square of health expenditure				0.004	0.004	0.010			
				[0.47]	[0.36]	[0.90]			
First lag of health expenditure							-0.008	0.019	0.011
							[1.07]	[1.69]	[0.85]
Income	**-0.042**	-0.023	-0.032	**-0.044**	-0.026	-0.030	**-0.034**	-0.023	-0.033
	[3.70]	[1.24]	[1.29]	[3.64]	[1.36]	[1.16]	[2.94]	[1.19]	[1.30]
State dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year dummies	×	✓	✓	×	✓	✓	×	✓	✓
State-specific trends	×	×	✓	×	×	✓	×	×	✓

Notes: The number of observations (number of live births) is 117088 in the rural sample and 35783 in the urban sample. These are marginal effects from a probit; significant coefficients are in bold. Standard errors are robust and clustered at the state level. Absolute t-statistics are in parentheses. State health expenditure and state income are real per capita measures cast in logarithms. Every equation includes state-specific positive and negative rainfall shocks and micro-demographic controls (dummies for child gender and birth-month, age of mother at birth of the child, level of education of each of mother and father, and ethnicity and religion of the household).

Table 2: Probit Estimates of Infant Mortality: Distributed Lag Model

	(1) Baseline	(2) Add rain-shocks	(3) Add state-controls
L(ln health expenditure)	0.012	0.008	0.006
	[1.38]	[0.96]	[0.75]
L2(ln health expenditure)	0.003	0.002	-0.005
	[0.23]	[0.16]	[0.44]
L3(ln health expenditure)	**-0.022**	**-0.020**	**-0.020**
	[2.39]	[1.94]	[1.84]
L4(ln health expenditure)	-0.007	-0.005	-0.008
	[0.71]	[0.45]	[0.64]
Long run marginal effect	-0.014	-0.015	**-0.027**
	[0.96]	[0.98]	[1.73]
Health expenditure elasticity	-0.148	-0.158	-0.285
L(ln ncome)	-0.018	-0.019	-0.027
	[1.10]	[1.24]	[1.62]
L2(ln income)	-0.006	-0.005	-0.007
	[0.47]	[0.44]	[0.56]
L3(ln ncome)	**-0.056**	**-0.056**	**-0.052**
	[4.14]	[4.73]	[5.52]
L4(ln income)	**0.031**	**0.034**	**0.031**
	[3.00]	[3.92]	[3.73]
Long run marginal effect	**-0.048**	**-0.047**	**-0.054**
	[2.07]	[2.06]	[2.55]
Income elasticity	-0.506	-0.496	-0.570

Notes: Rural sample, N=117088. Standard errors are robust and clustered at the state level. Absolute t-statistics are in parentheses. L denotes lag. Every equation includes state and year dummies, state-specific trends and the micro-demographic controls listed in Notes to Table 1. Column 2 further includes positive and negative state-specific rainfall shocks. The additional controls in Column 3 are the ratio of agricultural to non-agricultural output in the state, inflation of consumer prices for agricultural and industrial workers, the log poverty headcount ratio and the log of the Gini coefficient for each of the rural and urban sectors, and a quadratic in per capita newspaper circulation.

Table 3: Probit Estimates of Infant Mortality : Parsimonious Model With Significant Lags

	(1)	(2)	(3)	(4)
		No state-trends		**Include state-trends**
		Add state-X		**Add state-X**
L3(ln health expenditure)	-0.009	-0.016	-0.020	-0.023
	[0.67]	[1.46]	[2.17]	[2.86]
Health expenditure elasticity	-0.095	-0.169	-0.211	-0.243
L3(ln ncome)	-0.059	-0.058	-0.059	-0.057
	[2.89]	[3.66]	[4.31]	[5.30]
L4(ln income)	0.039	0.034	0.032	0.031
	[3.45]	[3.16]	[3.28]	[2.93]
Long run marginal effect	-0.020	-0.023	-0.027	-0.026
	[0.83]	[1.38]	[2.47]	[2.64]
Income elasticity	-0.212	-0.247	-0.283	-0.277

Notes: Rural sample, N=117088. Standard errors are robust and clustered at the state level. Absolute t-statistics are in parentheses. L denotes lag. Full results, showing the marginal effects of all covariates, are in Table A5 of the Online Appendix referred to in footnote 5. Every equation includes state and year fixed effects, rainshocks and micro-demographic controls. Columns 2 and 4 also include state-level controls; see Notes to Tables 1 and 2.

Table 4: Panel Data Estimates for the Infant Mortality Rate

	(1)	(2)
	4 lags	**Significant lags**
L(ln health expenditure)	0.005	
	[0.51]	
L2(ln health expenditure)	-0.014	
	[0.87]	
L3(ln health expenditure)	-0.022	-0.029
	[1.90]	[2.97]
L4(ln health expenditure)	-0.009	
	[0.92]	
Long run marginal effect	-0.040	-0.029
	[1.86]	[2.97]
Health expenditure elasticity	-0.425	-0.306
L(ln ncome)	-0.017	
	[0.83]	
L2(ln income)	0.007	
	[0.44]	
L3(ln ncome)	-0.054	-0.055
	[4.71]	[4.14]
L4(ln income)	0.028	0.028
	[2.07]	[2.06]
Long run marginal effect	-0.037	-0.027
	[1.55]	[1.50]
Income elasticity	-0.392	-0.282

Notes: These are within-group estimates on the state panel (see section 5.2). Columns 1 and 2 correspond to Table 2 (col.3) and Table 3 (col.4). These equations include state and year fixed effects, state-specific trends, rainshocks, micro-demographic and state-level controls. Standard errors are robust and clustered at the state level. Absolute t-statistics are in parentheses.

Table 5A
Heterogeneity in the Health Expenditure Effect by Population Sub-Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Sector		**Gender**		**Caste**			**Religion**		
	Rural	Urban	Boys	Girls	High caste	Low caste	ST	Hindu	Not Hindu	Muslim
L3(health expenditure)	**-0.020**	-0.010	**-0.026**	-0.016	***-0.020***	-0.016	**-0.089**	-0.019	-0.024	**-0.044**
	[2.17]	[1.06]	[2.20]	[1.14]	[1.87]	[1.16]	[3.12]	[1.75]	[1.45]	[2.33]
elasticity	-0.211	-0.108	-0.271	-0.168	-0.196	-0.158	-0.817	-0.189	-0.434	-0.694
Income	-0.027	0.051	-0.025	-0.032	-0.019	-0.027	0.035	-0.031	-0.013	-0.043
	[2.47]	[2.59]	[1.89]	[2.36]	[0.97]	[2.05]	[0.90]	[2.14]	[0.27]	[0.80]
elasticity	-0.283	0.537	-0.257	-0.342	-0.193	-0.315	0.375	-0.311	-0.173	-0.548
Mean of dep var	0.093	0.059	0.0939	0.0958	0.0835	0.0997	0.100	0.0987	0.0735	0.079
N	117088	35783	61002	56086	38360	77225	13820	98884	18204	13136
% of group	69	31	52.1	47.9	33.2	66.8	12.0	84.4	15.6	11.2

See Notes to Table 5B

Table 5B

Heterogeneity in the Health Expenditure Effect by Population Sub-Group (contd).

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
	Birth order		**Mother's education**			**Father's education**			**Maternal age at birth**		
	First born	Other	None	Some	Higher	None	Some	Higher	9-18	19-30	31-49
L3(health expenditure)	-0.009	**-0.023**	-0.014	**-0.035**	**-0.001**	-0.009	-0.009	-0.019	-0.006	**-0.028**	0.011
	[0.31]	[2.75]	[1.54]	[2.41]	[2.65]	[0.31]	[0.31]	[1.38]	[0.26]	[3.02]	[0.68]
Elasticity	-0.091	-0.245	-0.138	-0.738	-4.858	-0.091	-0.091	-0.402	-0.047	-0.403	0.160
Income	-0.034	-0.028	-0.031	-0.024	0.065	-0.018	-0.034	-0.020	0.000	-0.045	-0.078
	[1.57]	[1.94]	[2.37]	[1.24]	[0.46]	[0.72]	[2.10]	[0.48]	[0.01]	[3.92]	[1.09]
Elasticity	-0.353	-0.302	-0.299	-0.358	1.889	-0.173	-0.392	-0.284	-0.003	-0.511	-0.859
Mean of dep var	0.0968	0.0942	0.1042	0.0685	0.0346	0.0968	0.0968	0.0709	0.1223	0.0878	0.0904
N	26737	90351	86305	30783	4017	26737	26737	20505	22993	83818	10277
% of group	22.8	77.2	73.7	26.3	3.5	22.8	22.8	17.5	19.6	71.6	8.8

Notes: The specification estimated is that in column 3 of Table 3. Standard errors are robust and clustered at the state level. Absolute t-statistics are in parentheses. L3 denotes the third lag of log health expenditure p.c. The reported marginal effect for income is the long run effect derived from its third and fourth lag. Elasticities are calculated at the mean for the sub-group; these means are shown in the Table. Controls include state and year effects and state-specific trends, micro-demographics and rainfall shocks. Except in the case of column 2, the sample is restricted to rural households. The last row shows the sample percentage of each sub-group. The category "Not Hindu" includes Muslim, but I further show results for Muslims alone. Higher education is defined as completion of secondary or higher. The samples are created separately for mother's and father's education. In the sample of children whose fathers have no education, 93% of mothers have no education. However, in the sample whose mothers have no education, only 51% of fathers have no education.

Figure 1

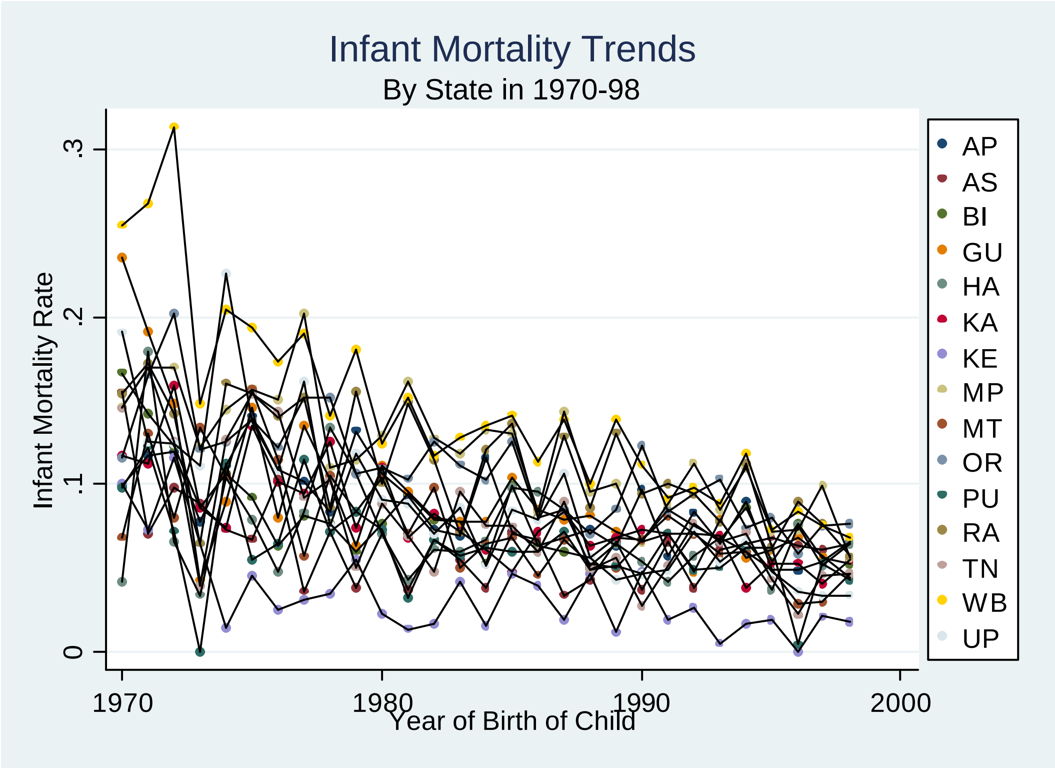


Figure 2

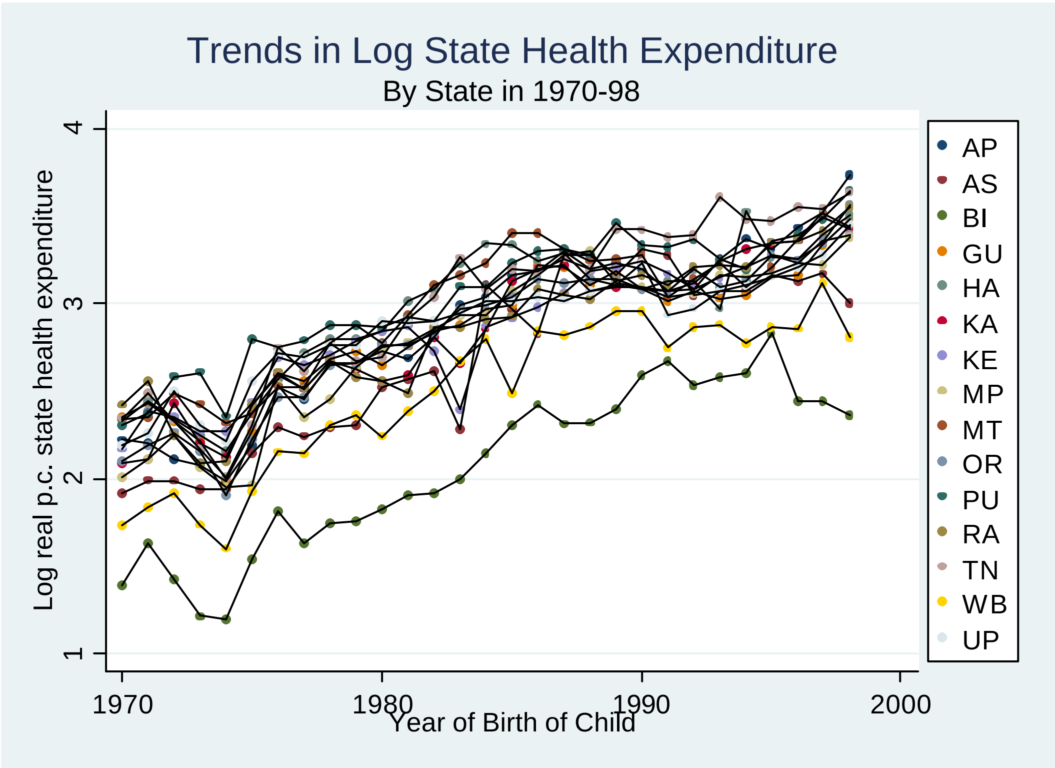


Figure 3

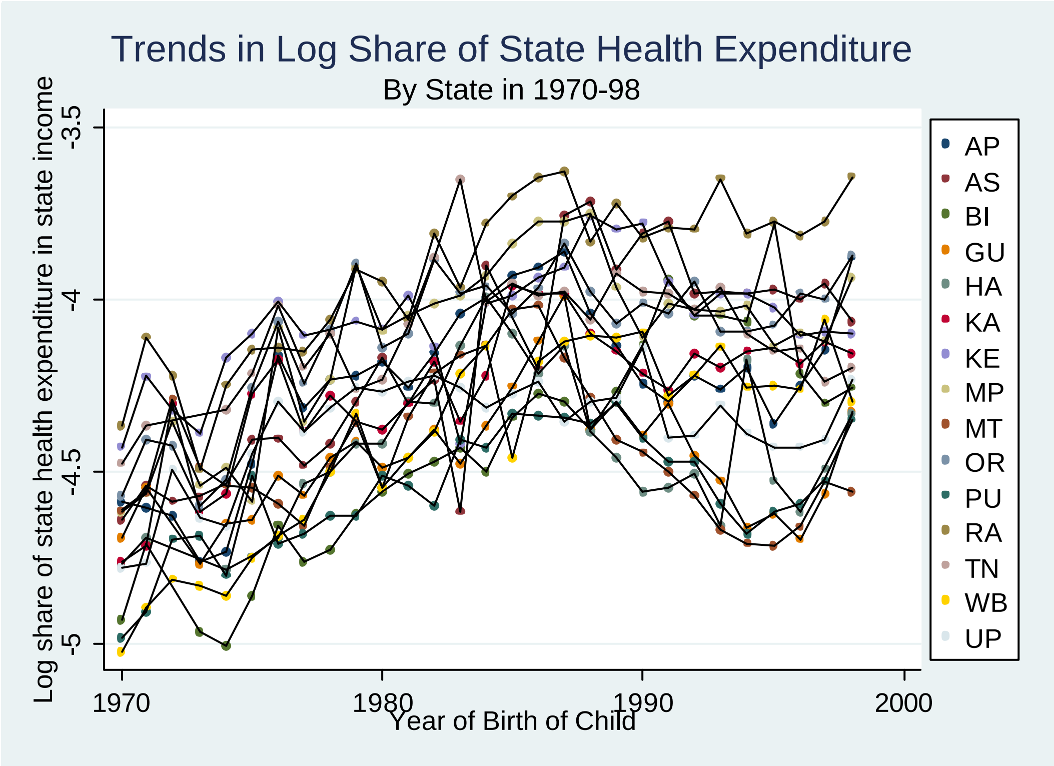


Figure 4

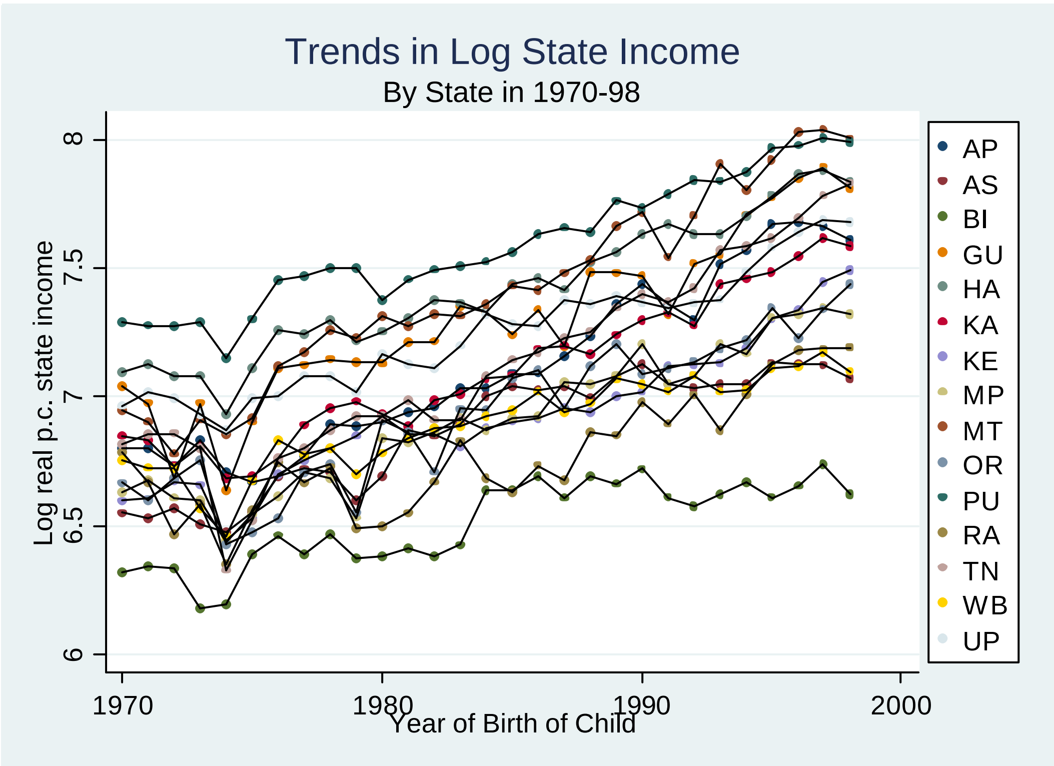


Figure 5

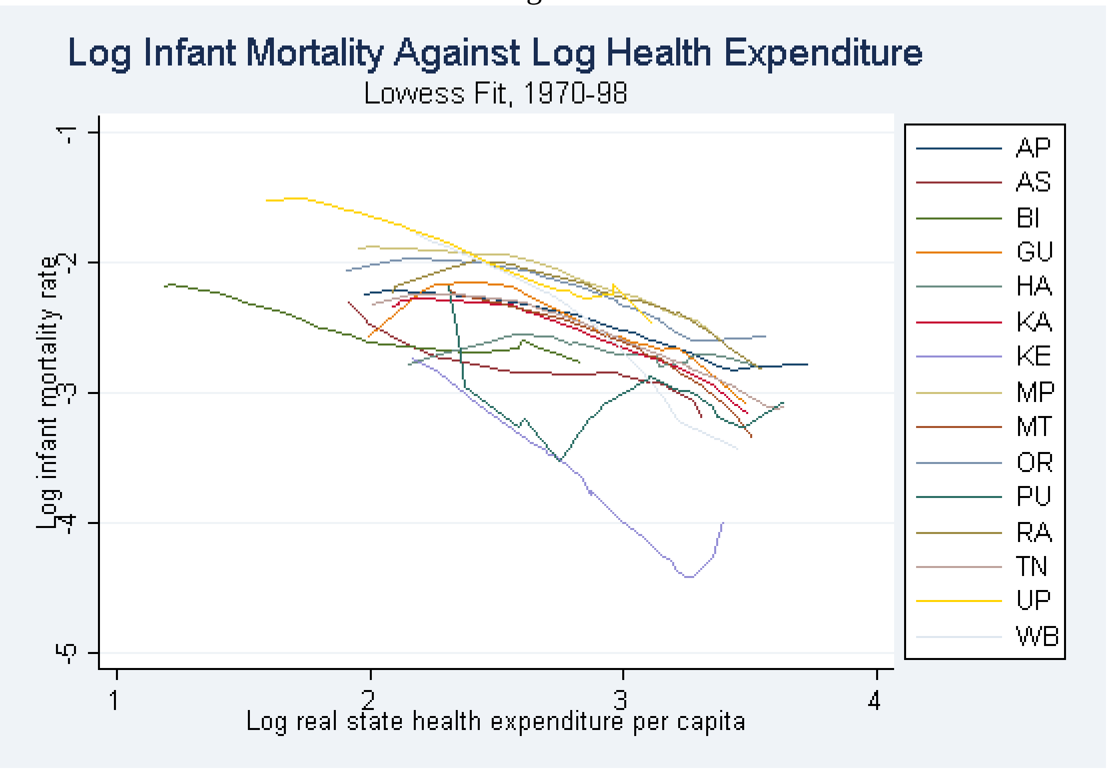
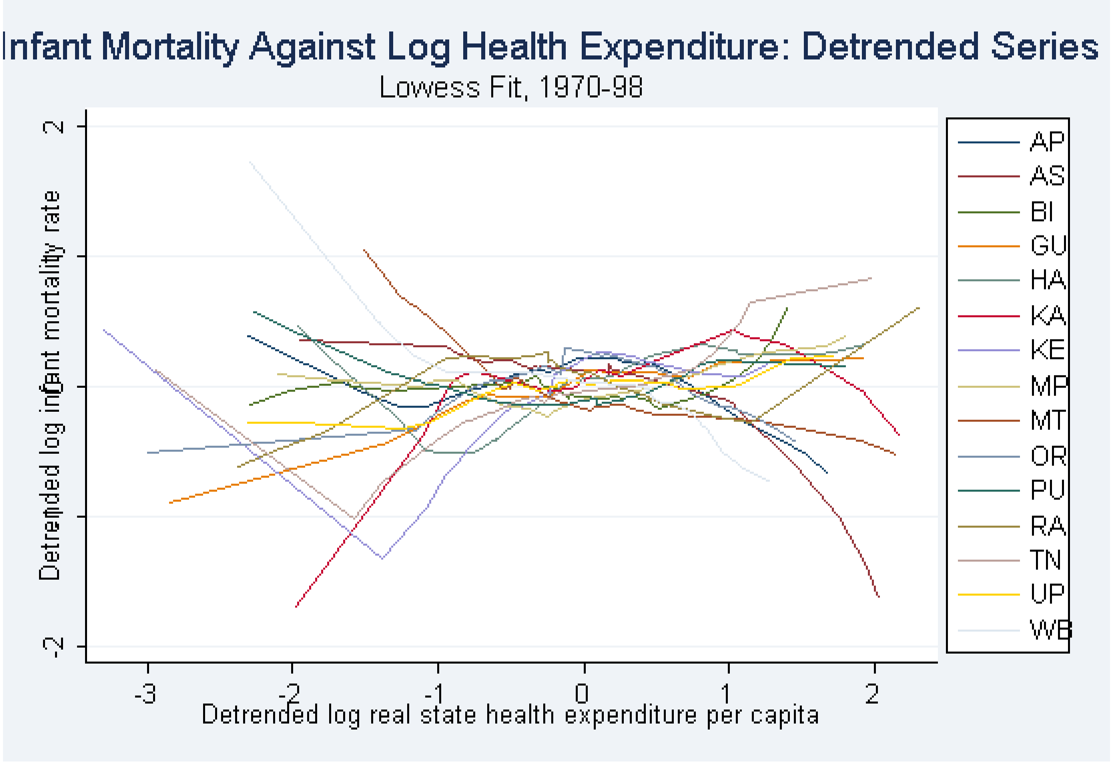


Figure 6



APPENDIX

Table A1: Average Annual Linear Rate Of Growth Of Main Variables in 1970-98. All Figures Are In Percentages

State	Infant mortality	Health expenditure	Health share	Income
Andhra	-2.86	5.45	1.70	3.75
Assam	-1.67	5.30	2.78	2.52
Bihar	-2.26	5.11	3.48	1.63
Gujarat	-2.87	4.00	0.46	3.54
Haryana	-1.04	4.09	1.09	3.00
Karnataka	-3.17	4.82	1.61	3.21
Kerala	-9.79	4.05	1.09	2.96
Madhya	-2.75	4.93	1.89	3.04
Maharashtra	-3.53	4.07	-0.26	4.33
Orissa	-2.79	4.82	1.73	3.10
Punjab	0.17	4.02	1.20	2.81
Rajasthan	-2.42	4.49	2.27	2.23
Tamil Nadu	-4.10	5.35	1.19	4.17
Uttar Pradesh	-4.11	4.77	2.86	1.91
West Bengal	-5.29	3.56	0.92	2.63
India	-3.23	4.59	1.60	2.99
s.d.	2.24	0.59	0.97	0.76

Notes: Growth rates are obtained by regression of the logarithm of the variable on a linear trend using the state panel with 29 years, 1970-98. The standard deviation of growth rates across states is denoted s.d. in the last row. Health expenditure and income are deflated and per capita. Health share is share of state health expenditure in state income. Most growth rates are significant at the 1% level. The exceptions are as follows. Infant mortality decline is insignificant in Punjab and Haryana. Growth in health share is insignificant in Gujarat and Maharashtra.

Table A2: Summary Statistics of Variables in the Analysis

Variable	Mean	Std. Dev.	Min	Max
log p.c. real health expenditure	2.85	0.45	0.66	3.79
log share of health expenditure in state income	-4.21	0.28	-6.14	-3.63
log p.c real net state domestic product	7.06	0.37	5.97	8.17
infant mortality	0.094	0.292	0	1
Child gender				
Male	0.521			
Female	0.479			
Child birth-month				
January	0.068			
February	0.065			
March	0.082			
April	0.079			
May	0.078			
June	0.085			
July	0.087			
August	0.106			
September	0.091			
October	0.095			
November	0.088			
December	0.076			
Mother's age at birth of index child				
9-15	0.036			
16-18	0.158			
19-24	0.468			
25-30	0.249			
31-49	0.090			
Mother's education				
None	0.733			
Incomplete primary	0.086			
Primary	0.060			
Incompete secondary	0.084			
Secondary or higher	0.037			
Father's education				
None	0.399			
Incomplete primary	0.122			
Primary	0.099			
Incompete secondary	0.202			
Secondary	0.093			
higher than secondary	0.085			
Ethnicity				
Higher castes	0.331			
Scheduled caste	0.207			
Scheduled tribe	0.121			
Other backward caste	0.341			
Ethnicity missing	0.013			
Religion				
Hindu	0.844			
Muslim	0.113			
Christian	0.013			
Other religion	0.006			

Notes: Income and health expenditure in the first three rows are available at the state level. All other statistics presented here are for the rural sample; statistics for the urban sample are available on request. Standard deviations are not provided for indicator variables. For indicators, the minimum and maximum values are 0 and 1, so these are not shown. The category that is excluded from the regression is italicised.

Table A3: State-Specific Estimates Using Current Health Expenditure

	Panel A: Include Trend			Panel B: No Trend		N
	health exp	Income	trend	health exp	income	
Andhra Pradesh	-0.032	-0.030	0.001	-0.025	-0.017	6025
	[1.2]	[0.59]	[0.31]	[1.53]	[0.62]	
Assam	***-0.028***	-0.019	***0.002***	-0.017	0.017	6246
	[1.63]	[0.36]	***[1.88]***	[1.04]	[0.35]	
Bihar	0.017	**-0.072**	***-0.001***	-0.002	**-0.065**	15978
	[1.23]	**[2.45]**	***[1.65]***	[0.3]	**[2.23]**	
Gujarat	0.002	-0.013	-0.002	-0.016	-0.037	5296
	[0.07]	[0.31]	[0.9]	[0.79]	[1.22]	
Haryana	-0.004	-0.023	-0.001	-0.007	-0.039	4969
	[0.18]	[0.3]	[0.23]	[0.38]	[1.19]	
Karnataka	-0.030	0.096	-0.004	**-0.054**	0.037	6338
	[1.06]	[1.45]	[1.29]	**[2.34]**	[0.84]	
Kerala	0.004	0.022	-0.002	-0.017	-0.013	2920
	[0.16]	[0.51]	[1.3]	[0.74]	[0.41]	
Madhya	-0.001	-0.058	-0.002	-0.009	**-0.091**	13445
	[0.08]	[1.26]	[0.94]	[0.62]	**[3.04]**	
Maharashtra	**-0.062**	-0.047	0.003	**-0.052**	-0.002	4660
	[2.82]	[0.81]	[0.83]	**[2.86]**	[0.1]	
Orissa	-0.010	-0.009	-0.002	-0.031	-0.026	7679
	[0.33]	[0.2]	[1.14]	[1.38]	[0.66]	
Punjab	-0.030	-0.011	0.001	-0.026	0.001	3939
	[0.88]	[0.14]	[0.2]	[0.97]	[0.03]	
Rajasthan	0.000	-0.055	-0.001	-0.016	**-0.057**	13685
	[0.01]	[1.96]	[0.51]	[1.28]	**[2.04]**	
Tamil Nadu	-0.025	0.043	-0.004	***-0.051***	-0.006	4679
	[0.81]	[0.81]	[1.32]	***[1.95]***	[0.18]	
Uttar Pradesh	-0.028	0.077	**-0.005**	**-0.067**	-0.010	20975
	[1.5]	[1.24]	**[4.85]**	**[3.81]**	[0.17]	
West Bengal	**-0.113**	0.007	0.001	**-0.101**	0.032	5132
	[2.93]	[0.11]	[0.63]	**[3.19]**	[0.59]	
India	0.004	**-0.032**		0.002	-0.011	195365
	[0.47]	**[2.46]**		[0.21]	[0.42]	

Notes: Absolute robust t-statistics are in parentheses. Significant coefficients are in bold. Panel A shows results from a model that also includes a trend, the analogue of the model that includes state-specific trends when the data are pooled, as in Tables 1-4. The trend is not significant in most states. Panel B shows results obtained after dropping the trend. To obtain the all-India coefficients, I condition upon state dummies and time dummies and, in parallel with the state-specific results, include state-specific trends in Panel A but not in Panel B. There are no other control variables (X) in these models.

Table A4: Alternative Estimators & Standard Error Adjustments

	No state-specific trends			Add state-specific trends			
	none	**robust**	**cluster**	**none**	**robust**	**cluster**	**LPM**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Health expenditure	0.009	0.009	0.009	0.002	0.002	0.002	-0.000
	[1.16]	[1.16]	[0.80]	[0.19]	[0.20]	[0.14]	[0.03]
Income	**-0.021**	**-0.021**	-0.021	**-0.029**	**-0.029**	**-0.029**	**-0.027**
	[2.22]	[2.22]	[0.88]	[2.17]	[2.17]	[2.09]	[2.26]

Notes: This is the model in Table 1 with current log health expenditure and log income as key regressors. It is run for rural households, N=117088. Absolute t-statistics are in parentheses. Every column contains state and year dummies. Columns 1-3 and 4-6 show that clustering the standard errors by state raises them substantially if state trends are excluded. Column 7 shows the specification in column 6 estimated by the Linear Probability Model rather than the probit. The coefficients on income and health expenditure in the LPM are a bit smaller than but not significantly different from the corresponding probit marginal effects.

Table A5: Parsimonious Model With Significant Lags

	(1)	(2)	(3)	(4)
	No state-trends		Include state-trends	
		Add state-X		**Add state-X**
L3(ln health expenditure)	-0.009	-0.016	-0.020*	-0.023**
	[0.67]	[1.46]	[2.17]	[2.86]
Health expenditure elasticity	-0.095	-0.169	-0.211	-0.243
L3(ln ncome)	-0.059**	-0.058**	-0.059**	-0.057**
	[2.89]	[3.66]	[4.31]	[5.30]
L4(ln income)	0.039**	0.034**	0.032**	0.031**
	[3.45]	[3.16]	[3.28]	[2.93]
Long run marginal effect	-0.020	-0.023	-0.027	-0.026
	[0.83]	[1.38]	[2.47]	[2.64]
Income elasticity	-0.212	-0.247	-0.283	-0.277
ln (state population)	-0.006	0.045	-0.051	0.003
	[0.14]	[0.69]	[0.21]	[0.02]
1 if female	0.002	0.002	0.002	0.002
	[0.81]	[0.79]	[0.82]	[0.80]
Child birth month (base=January)				
February	-0.006	-0.007	-0.006	-0.007
	[1.31]	[1.50]	[1.30]	[1.50]
March	-0.007	-0.007	-0.007	-0.007
	[1.56]	[1.51]	[1.59]	[1.54]
April	-0.001	-0.001	-0.001	-0.001
	[0.16]	[0.16]	[0.16]	[0.17]

May	-0.005	-0.004	-0.005	-0.005
	[0.77]	[0.74]	[0.79]	[0.77]
June	0.001	0.001	0.001	0.001
	[0.21]	[0.26]	[0.20]	[0.23]
July	0.001	0.001	0.001	0.001
	[0.17]	[0.23]	[0.16]	[0.21]
August	0.005	0.005	0.005	0.005
	[1.17]	[1.17]	[1.16]	[1.15]
September	-0.001	-0.001	-0.001	-0.001
	[0.23]	[0.20]	[0.23]	[0.20]
October	-0.003	-0.003	-0.003	-0.003
	[0.83]	[0.80]	[0.83]	[0.80]
November	-0.008	-0.008	-0.008	-0.008
	[1.47]	[1.42]	[1.46]	[1.43]
December	-0.003	-0.003	-0.003	-0.003
	[0.59]	[0.57]	[0.60]	[0.58]
Birth order of child (base=1)				
2	-0.004	-0.004	-0.004	-0.004
	[1.37]	[1.37]	[1.40]	[1.38]
3	0.000	0.000	0.000	0.000
	[0.16]	[0.10]	[0.07]	[0.06]
4	0.011**	0.011**	0.010**	0.011**
	[4.45]	[4.47]	[4.42]	[4.48]
5 or more	0.016**	0.016**	0.016**	0.016**
	[8.59]	[8.57]	[8.48]	[8.49]
Maternal education (base=none)				
Incomplete primary	-0.008	-0.008	-0.008	-0.008

	[1.86]	[1.84]	[1.81]	[1.81]
Complete primary	-0.011**	-0.011**	-0.010**	-0.011**
	[2.86]	[2.91]	[2.80]	[2.84]
Incomplete secondary	-0.015**	-0.016**	-0.015**	-0.016**
	[3.81]	[3.94]	[3.90]	[4.00]
Secondary or higher	-0.035**	-0.035**	-0.036**	-0.036**
	[5.00]	[5.12]	[5.15]	[5.21]
Paternal education (base=none)				
Incomplete primary	-0.002	-0.002	-0.002	-0.002
	[0.60]	[0.58]	[0.58]	[0.56]
Complete primary	-0.004	-0.004	-0.004	-0.004
	[1.03]	[1.09]	[1.04]	[1.08]
Incomplete secondary	-0.013**	-0.013**	-0.013**	-0.013**
	[5.72]	[5.81]	[5.79]	[5.78]
Complete secondary	-0.023**	-0.022**	-0.022**	-0.022**
	[7.07]	[6.95]	[7.08]	[7.01]
Post-secondary	-0.019**	-0.019**	-0.019**	-0.018**
	[4.25]	[4.21]	[4.30]	[4.23]
Caste (base=upper caste)				
Scheduled caste	0.010**	0.010**	0.010**	0.010**
	[3.37]	[3.41]	[3.36]	[3.36]
Scheduled tribe	0.003	0.003	0.003	0.003
	[0.58]	[0.65]	[0.58]	[0.64]
Other backward caste	0.006	0.006	0.006	0.006
	[1.91]	[1.88]	[1.92]	[1.87]
Religion (base=Hindu)				
Muslim	-0.007	-0.007*	-0.007	-0.007

	[1.88]	[1.96]	[1.92]	[1.96]
Christian	-0.007	-0.008	-0.006	-0.007
	[0.70]	[0.81]	[0.67]	[0.76]
Other religion	-0.019**	-0.018**	-0.018**	-0.018**
	[2.95]	[2.93]	[2.96]	[2.95]
Maternal age at birth				
(base=19-24 years)				
9-15 years	0.053**	0.053**	0.052**	0.052**
	[10.26]	[10.34]	[10.24]	[10.26]
16-18 years	0.024**	0.024**	0.024**	0.024**
	[10.51]	[10.89]	[10.47]	[10.69]
25-30 years	-0.013**	-0.013**	-0.013**	-0.013**
	[8.32]	[8.53]	[8.25]	[8.67]
31-49 years	-0.010**	-0.009**	-0.010**	-0.010**
	[5.87]	[5.66]	[5.64]	[5.63]
State-level variables				
ln ratio of agri to nonagri product		-0.002		0.004
		[0.19]		[0.39]
inflation in prices in agri		-0.037		-0.031
		[1.81]		[1.50]
inflation in prices for industrial workers		0.178**		0.168**
		[2.83]		[2.65]
log rural poverty headcount rate		0.006		-0.007
		[0.43]		[0.81]
log urban poverty headcount rate		-0.017*		-0.001
		[2.29]		[0.12]

ln Gini in rural areas	-0.013	0.007
	[0.91]	[0.64]
ln Gini in urban areas	0.013**	0.012**
	[3.94]	[3.72]
ln newspaper circulation	-0.081**	-0.052*
	[2.72]	[2.36]
square of log newsp circulation	-0.011**	-0.006
	[2.78]	[1.69]

Notes: The key results from this Table are in Table 3 of the paper. Here I show the coefficients on all of the other covariates. This is the rural sample with N=117088. L denotes lag. Every equation also includes state and year fixed effects and positive and negative state-specific rainfall shocks (not displayed).

Figure A1

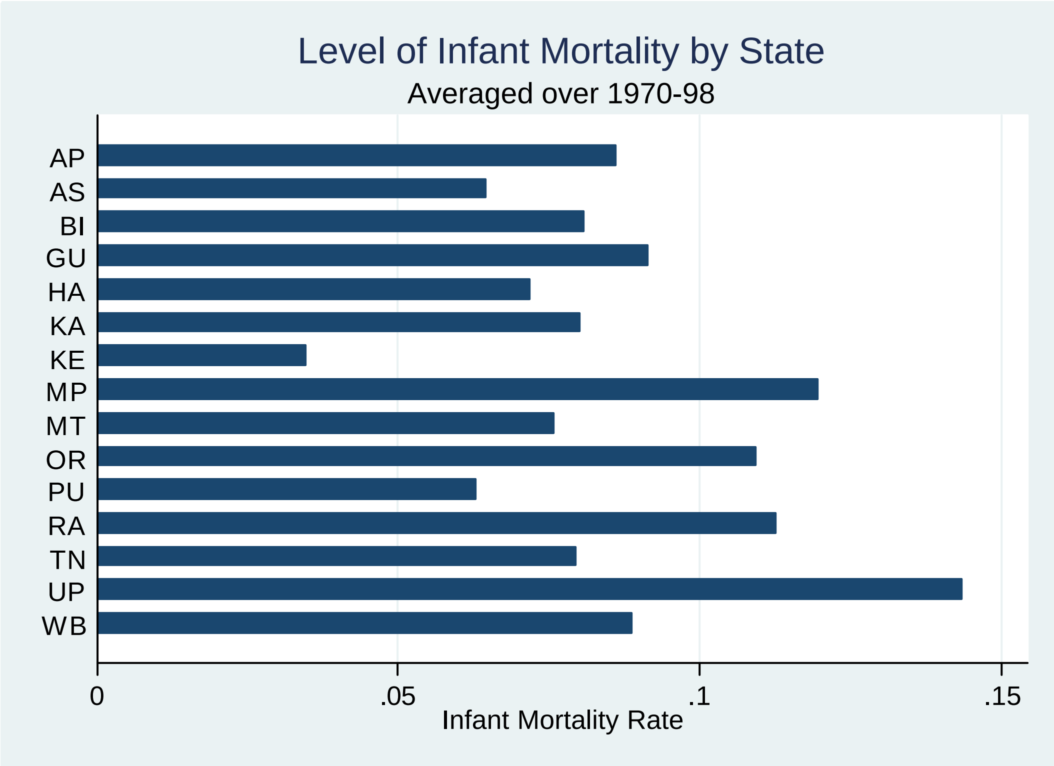


Figure A2